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The economic costs of oligopoly in the markets of rare earth minerals

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Abstract

In this research, the costs of rare earth elements (REEs) due to the oligopolistic market structure are estimated. On the supply side, China exercises a dominant position in the international REEs market because it controls more than 40 % of deposits and more than 60 % of REEs traded. Other countries assume an ancillary role in international markets for these minerals, which will increasingly play a crucial role in economic growth in the coming decades, since REEs are considered the minerals of technology and the green transition. Using the fringe oligopoly model, the costs due to this market structure for economies less endowed with deposits of these minerals are estimated. To perform this analysis, the Herfindahl-Hirschman Index was calculated, and a new index of dependence on REEs, as a proxy for a country's economic vulnerability, was constructed. Our database covers fifty years and sixty-two countries. Most of the data used comes from the World Bank database. Using quantile econometric models, we can calculate the economic costs of countries with fewer REEs caused by the market power exerted by the leading country in this market and estimate the loss for each country involved in the international trade of these minerals. Finally, technological advancements play a pivotal role in aiding countries reliant on REEs to lower their costs. This can be achieved through policies aimed at minimizing the utilization of REEs during manufacturing, harnessing the recycling of minerals from used products, and discovering alternative materials to replace REEs.

JEL Classification: D43; Q32; Q48

Keywords: GDP; Oligopoly with fringe; Quantile regression analysis; Rare Earths Elements (REEs); Green energy transition

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1. Introduction

Energy markets of non-renewable resources are often characterized by oligopoly with fringe structures, where a few dominant firms (i.e., the core) control most of the market power, while smaller firms (i.e., the fringe) also operate. The core firms significantly influence prices and output, often setting the market through strategies like price leadership or competitive tactics, while fringe firms, typically with fewer resources, adapt to the core's actions (e.g., Benchekroun et al., 2023).

In this paper, we analyze the oligopoly with fringes in the international market of Rare Earth Elements to estimate the social costs of the market power exercised by oligopolistic countries. Rare Earth Elements (hereinafter REEs) represent the most advanced frontier of natural resource constraints to growth and in reducing environmental depletion, including global warming (Benchekroun et al., 2023). REEs are a group of 17 non-renewable metal elements, but under some circumstances recyclable (e.g., Binnemans et al., 2013; Lai et al., 2024). They are used in defense technologies, including missiles, lasers, vehicle-mounted systems such as tanks, and military communications (Zhou et al., 2017), as well as in civil applications for electric power transmission and storage through superconductors, solar panels, wind turbines, batteries, microprocessors, and other devices (Voncken, 2016), playing a significant role in the green energy transition (Alfaro et al., 2025; Ghorbani et al., 2024).

These minerals are expected to increase demand in the future, leading to a rise in their prices. Being exhaustible natural resources, the sole or few owners of REEs deposits will earn a gradually increasing rent in the future as the scarcity of REEs rises (Jowitt, 2022; Stiglitz, 1974). It is expected that the worldwide requirement for REEs will experience a significant deficit, estimated at around 47,000 tons, by 2023 (Lai et al., 2024).

The endowment of these elements constitutes, like the deposit of other minerals, a non-tradable natural input, while what can be traded is the flow of extracted REEs. Thus, REEs can be considered a source of macroeconomic inefficiency both within a country's domestic borders and among economies involved in the global commerce of such natural inputs. From the perspective of international trade, the inequality in the distribution of REEs deposits is unfair. Countries with richer endowments of REEs can extract high levels of rent from international trade.

The costs of oligopoly and monopoly in the REEs market are high, as is the dependence on importing these minerals, indicating a reliance on foreign suppliers. Currently, China produces 60 % of the world's rare earth elements but processes nearly 90 %, importing and processing them from other nations. This has resulted in a quasi-monopolistic situation for China (Fan et al., 2023). The literature on energy economics lacks a prior analysis of the international oligopoly of rare earths and its economic impact. Only a few studies have addressed the problem of oligopoly in markets for exhaustible resources (Benchekroun et al., 2023), but no prior analyses have been performed on the market power exercised at a macroeconomic level by a single country worldwide. Despite the extensive investigation of REEs in economic literature, particularly from a microeconomic perspective (e.g., Voncken, 2016), the impact of the unequal distribution of REEs at the macroeconomic level and in terms of national economic growth has not yet been explored. Therefore, this research aims to fill this gap in the literature and develop a comprehensive framework that describes the relationship between the unequal distribution of REEs and the economic performance of countries dependent on REEs from oligopolistic nations.

First, we develop a new index of inequality in the endowment of REEs deposits among countries as an alternative measure to the Gini Index or the Herfindahl-Hirschman Index (HHI), which are popularly used in this research area to map the geopolitical risk of RE supplies (Althaf & Babbitt, 2021; Goe & Gaustad, 2014; Santillán-Saldivar et al., 2021). Our new index calculates the distance of a single country's endowment relative to the average of all national economies involved in international trade of RE minerals. However, the raw indicator of REEs dependence is weighted by population, a proxy of scale and wealth level of a country, as measuring REEs dependence in absolute terms is not meaningful without considering each country's stage of development and overall economic reliance on these minerals.

Second, we employ an original balanced panel dataset that covers fifty years, from 1973 to 2022, considering sixty-two countries. Most of the data used was drawn from the World Development Indicators (WDI) held by the World Bank (WDI, 2024). Additionally, we adopt quantile regression analysis to evaluate the heterogeneous effects of the unequal distribution of REEs on the gross domestic product (GDP) and per capita GDP (GDPPC) of countries worldwide—located in low (.10 and.25), middle (.50), and high (.75 and.90) quantiles—mainly focusing on developing and developed countries. This involves comparing countries at the bottom of the ranking with those characterized by a high level of REEs endowment. In this way, it is possible to measure the comprehensive loss of global wealth due to this inequality and how a more equal distribution of REEs could increase welfare.

The results of our research are twofold. First, there is a negative relationship between the unequal distribution of REEs and economic performance across countries located in the low (.10 and.25) and medium (.50) quantiles only. In contrast, there is a positive relationship between the unequal distribution of REEs and the economic performance of countries located in the high (.75 and.90) quantiles. Thus, the effects of the unequal distribution of REEs are heterogeneous across countries and are mainly experienced by developing (low quantiles) rather than developed (high quantiles) countries. Second, we calculate the costs of oligopoly in the REEs market, assuming China and a few other countries (e.g., Australia, Brazil, India, Russia, the US, and Vietnam) as oligopolists. We find evidence that the cost of oligopoly and economic performance vary in magnitude across countries placed in the low (.10 and.25), medium (.50), and high (.75) quantiles. Given the income level of each country, developing countries—especially those in the lowest quantiles—are more adversely affected than the most developed ones—located in the highest quantile—by the oligopolistic behavior of China and a few other nations with REEs.

In light of these findings, several policy implications arise. Considering the significant variability, it is essential to implement policy interventions in countries most affected by oligopolistic behavior in the REEs market. Such policies should aim to fill economic growth gaps to reduce REEs supply risk, promoting alternative pathways including: i) circular economy strategies, ii) building supply chain agility, iii) developing domestic supply based on green alternative sources, and iv) exploring beyond terrestrial mining.

The remainder of the paper is organised as follows. Section 2 discusses the literature background beyond the REEs topic. Section 3 describes the data and method used. Section 4 presents the empirical model, while Section 5 reports the main results. Section 6 discusses the main findings. Finally, Section 7 concludes the paper.

2. Background

In the global development of energy sustainability and low-carbon goals to achieve emissions reduction targets, minerals are seen as the vitamins for the green energy transition. The criticality of raw materials has become a common issue in planning the shift from fossil fuel energy to low-carbon energy. Indeed, the past decade has seen several countries establish critical raw materials lists, including minerals essential to the development of low-carbon energy technologies.

Considering this varied category of elements, critical metals (e.g., cobalt, lithium, nickel, platinum, rare earth, tungsten) are widely used in strategic sectors for economic growth and national security, being employed in industry such as healthcare, electronics, aerospace, and clean energy (Gao et al., 2024; Alfaro et al., 2025). Among them, rare earth metals possess a range of distinctive properties, such as superconductivity and ferromagnetism, which make them particularly suitable for adoption in the renewable and green industries (Fan et al., 2023; Song et al., 2021). Despite their name, they are not rare in absolute terms, but their rarity depends on the difficult extraction and production process (Fan et al., 2023; Salim et al., 2022; Wübbeke, 2013). Rare earth elements are a group of 17 chemical elements, including 15 lanthanides (lanthanum, cerium, praseodymium, neodymium, promethium, samarium, europium, gadolinium, terbium, dysprosium, holmium, erbium, thulium, ytterbium, lutetium) and scandium and yttrium. REEs are grouped into one family of elements due to their chemical similarities (e.g., Wang et al., 2020; Lai et al., 2024) but are divided into two sub-categories: light rare earths (cerium, lanthanum, praseodymium, neodymium, promethium, europium, gadolinium and samarium), and heavy rare earths (dysprosium, yttrium, terbium, holmium, erbium, thulium, yttrium and lutetium).

However, their diffusion on the planet is not homogeneously spread but is concentrated in few countries (Australia, China, USA), with China owing more than 60 % and processing about 90 % of global market share (Barteková & Kemp, 2016; Fan et al., 2023; Song et al., 2021), with few other countries producing smaller quantities, as reported by Fig. 1, creating an oligopoly with fringes market structure.

While until the 1990s, the United States held the position of the world's top producer of rare earth elements, by the mid-1990s, China had overtaken the U.S. and emerged as the leading global producer (Wang et al., 2020; Wübbeke, 2013). Indeed, the country acts as quasi quasi-monopolist in the international market of REEs, in consideration of the huge ore deposit it holds and the great amount of intermediate input it produces, causing the other countries with a scarce or no endowment of REEs to sustain high costs due to the existing market structure. As Chinese President Xiaoping stated in 1992, according to the China National Radio, "there is oil in the Middle East; there is rare earth in China" (Biedermann, 2014). Indeed, the REEs are not the first case in the history of economics in which a country, or a group of them, exercises a strong market power, like a monopolistic seller. During the first oil crisis, 1973–1974, the fossil fuel market acted like an oligopoly, with a dominant firm constituted by the Organization of the Petroleum Exporting Countries (OPEC), and a competitive fringe of other countries that supply a small percentage of the oil on the international market.[1] Table 1 reports reserves of rare earths in metric tons by country.

[1] See Harkness (1985) for a theoretical study on the relationship between the oil-producer group of countries OPEC and the oil-consumer group of countries OECD.

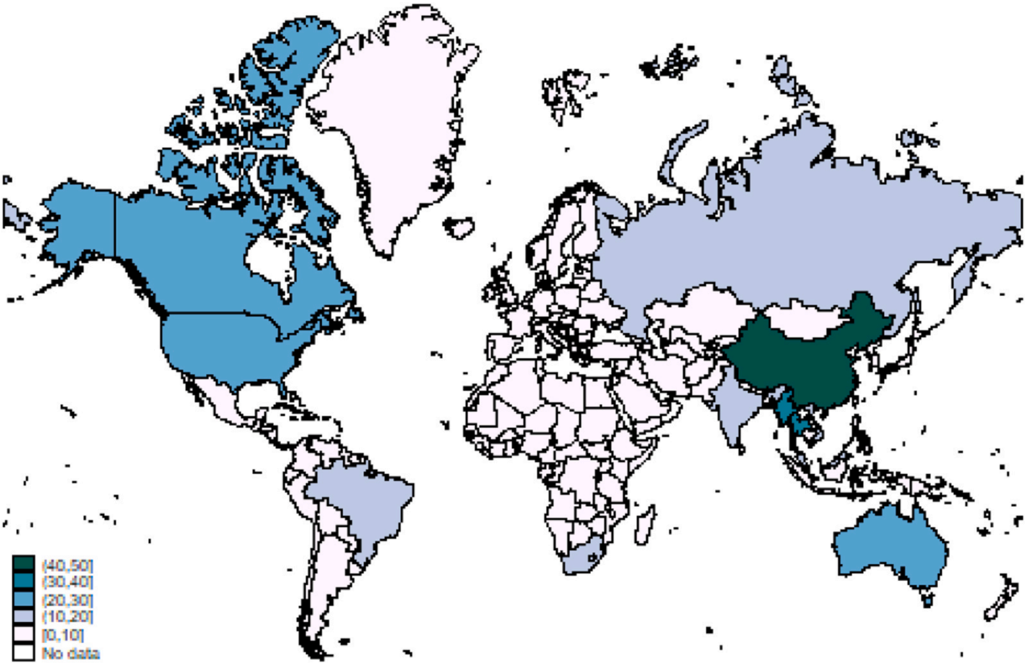

Fig. 1. Distribution of Rare Earth Elements (REEs%) worldwide by country (2023). Source: Author's elaboration on data sourced from https://www.statista.com/ with STATA.

In recent times, greater and greater attention has been paid to the geopolitical risk (Caldara & Iacoviello, 2022) concerning renewable energy (Cai & Wu, 2021), with a particular attention toward the REEs market (Zhou et al., 2020). In this sense, according to the U.S. "Going Critical" Geological Survey (USGS), "REEs are necessary components of more than 200 products across a wide range of applications, especially high-tech consumer products, such as cellular telephones, computer hard drives, electric and hybrid vehicles, and flat-screen monitors and televisions, and also significant defense applications including electronic displays, guidance systems, lasers, radar, and sonar systems." Even if the quantity of rare earth elements in a product is minimal in terms of weight, value, or volume, these elements can still be essential for the proper operation of the device. Rare earth element-based magnets typically make up only a minor portion of the overall weight, yet they are crucial for enabling the functionality of spindle motors and voice coils in desktops and laptops (Burton, 2022). As a result, leading countries and economies worldwide compete intensely for REEs endowment and trade (Zhou et al., 2020).

3. Data and method

3.1. Sample construction

The data consists of a balanced panel dataset used to analyze the relationship between REEs endowment and GDP growth rate for each country. The observation unit is the country for

Table 1
Reserves of rare earths worldwide (in 1000 metric tons REO) by country (2023).

Country	Reserves of rare earths in 1000 metric tons REO	Reserves of rare earths in percentage (%) of the total
China	44.00	0.37
Vietnam	22.00	0.19
Russia	21.00	0.18
Brazil	10.00	0.084
India	6.9	0.058
Australia	5.7	0.048
Tanzania	4.5	0.038
United States	1.8	0.015
Greenland	1.5	0.013
Canada	0.83	0.007
South Africa	0.79	0.007
Thailand	0.045	0.0004

Source: https://www.statista.com/statistics/270277/mining-of-rare-earths-by-country/

which all aggregated data are used. The resulting 3100 observations correspond to all combinations involving 62 countries worldwide from 1973 to 2022.

Countries considered whether they have or do not have natural REEs endowments, including both developed and developing countries. These classifications are based on the World Bank's definition, which uses Gross National Income (GNI) per capita evaluated with the Atlas method. Developed countries are those with GDP per capita greater than or at least equal to 12,055 US dollars (2016) and are reported in group A of Table 2. Developing economies have GDP per capita lower than the threshold mentioned above, and are listed in part B of Table 2.

In addition to the dependent variable of a country's economic growth rate and the main independent variable of the Index calculating the REEs distribution in each country, other economic values such as net investment cash flow, mineral depletion rate (%), and fossil fuel energy consumption rate (%); innovation-related values such as research and development expenditure rate (%), education, and patent applications; and local-related factors such as institutional quality, political stability, and country effects are all included in the analysis and further discussed in subsection *Other control variables*. The main sources of data are the World Bank, World Bank-WGI, OECD National Accounts, OECD-IEA, UNESCO National Accounts, and World Intellectual Property Organization (WIPO).

Finally, Tables A.1–A.4 in Appendix A provide additional information on the data sources, descriptive statistics, variables' correlation matrix, and partial and semi-partial correlation matrices.

3.2. Dependent variable

Alternative energy resources' exploitation is related to economic growth since energy is an indispensable input in the aggregate production function (Yıldırım et al., 2014). As the World scrambles with the urgent need to decarbonize energy systems and address the challenges of climate change, the pivotal role of renewable energy technologies has come to the forefront (Apergis & Apergis, 2017). Their central role in achieving the transition towards more sustainable and environmentally friendly growth has become increasingly evident (Abbas et al., 2024). In the last two decades, there has been an unprecedented surge in global demand for

Table 2
List of countries divided by GNI per capita.

A. DEVELOPED COUNTRIES	B. DEVELOPING COUNTRIES
Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia♣, Finland, France, Germany, Greece, Greenland♣, Iceland, Ireland, Italy, Japan♣, Luxembourg, Montenegro, Netherlands, Norway, Portugal, Russian Federation♣, Slovenia, Spain, Sweden, Switzerland, Thailand♣, Ukraine, United Kingdom, United States, Vietnam♣.	Albania, Argentina, Armenia, Azerbaijan, Bosnia and Herzegovina, Brazil♣, Bulgaria, Chile♣, China♣, Croatia, Hungary, India, Kazakhstan♣, Kosovo, Latvia, Lithuania, North Macedonia, Madagascar♣, Malaysia♣, Mexico, Myanmar♣, Moldova, Poland, Romania, Russia, Serbia and Montenegro, Slovakia, Turkey, Uruguay, Venezuela.

Note: *Low-income economies. ♣Countries are miners and exporters of rare earths.
Source: World Bank

renewable energy technologies, underscoring their critical importance in shaping the future of energy production and consumption (Chica-Olmo et al., 2020). Simultaneously, the global extraction and trade of rare earth elements (REEs) have reached record highs, driven by their essential role in high-tech applications and technological products, influencing a country's growth (Abbas et al., 2024).

To investigate the relationship between countries' natural REEs endowments and their economic performance, we adopt two traditional economic variables as dependent variables: *GDP growth rate* and *GDP per capita growth rate*. First, the Gross Domestic Product (GDP) growth rate (%), sourced from the World Bank and OECD National Accounts, is the annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are calculated using constant 2010 U.S. dollars. Second, the Gross Domestic Product Per Capita (GDPPC) growth rate (%), sourced from the World Bank and OECD National Accounts, is divided by the midyear population and based on constant local currency.

Although intuitively, low levels of REEs endowments negatively influence a country's growth rate, this study investigates whether the unequal distribution of REEs can have heterogeneous effects on economic growth for countries worldwide.

3.3. Main independent variable

Since part of the production related to technological products depends heavily on natural resources, REEs endowment measures may constrain the economic growth of countries with low or zero levels of REEs. Therefore, policymakers need to know the approximate distribution of REEs across countries, considering the oligopoly of REEs by China and a few other countries worldwide (Fan et al., 2023). To compare the inequality in REEs endowment distribution among countries worldwide, we developed a novel index to evaluate the distance from the average REEs endowment of economies with REEs resources. A three-step approach is adopted. First, we calculate the weighted REEs dependence indicator by multiplying the natural REEs endowment with the total population between the ages of 15–64 of each country i at time *t as* follows:

$$W_{REEs} = \text{REEs}endowment_{it} \times population_{it} \quad (1)$$

The reasons to use *population* as a weight factor are threefold: first, W_{REEs} ensures that the measure of inequality reflects disparities affecting a larger share of the global population. Second, it permits smooth comparability of REEs endowments across countries; third, the size of the population influences demand for REEs materials and economic resilience. A country with a low REEs endowment but a large population may face greater supply chain vulnerabilities compared to a less populous nation.

Then, we compute the mean ($\bar{W}_{REEs}$) and the standard deviation (σ_W) of the $W_{REEs,it}$ to determine the absolute distance of each country's weighted REEs endowment from the average REEs endowment:

$$D_{REEs} = |W_{REEs} - \bar{W}_{REEs}| \tag{2}$$

Finally, we normalize the distance (D_{REEs}) by dividing it with the standard deviation (σ_W) of the W_{REEs} to ensure the comparability across different countries i at time t.

$$Inequality_{REEs} = \sum \frac{D_{REEs}}{\sigma_W} \tag{3}$$

The obtained Inequality Index of REEs endowment (I_{REEs}) for country i at time t represents an unprecedent measure that accounts for the distance between a country's REEs endowments and those of reference countries with REEs, such as China and a few others. Since it is normalized, the index typically ranges from 0 to 1. High values of I_{REEs} (close to 1) indicate a greater distance from the reference countries with high levels of REEs endowment, while low values of I_{REEs} (close to 0) suggest a smaller distance from the reference countries with high levels of REEs endowments.

To assess the validity of the index denoting the distribution of REEs across countries, an alternative measure is used: the *Herfindahl-Hirschman Index* (HHI) for REE endowment and trade markets. The HHI index is commonly used in this research area to identify geopolitical risks of REE supplies (Althaf & Babbitt, 2021; Goe & Gaustad, 2014; Santillán-Saldivar et al., 2021). Measuring geopolitical risks is crucial for mapping the location and concentration of REE production where national interests may conflict with the importing country or where unstable socio-political situations could potentially disrupt the supply chain (Salim et al., 2022). Few studies have proposed a modified HHI index by coupling it with other factors, such as concentration factors (Achzet & Helbig, 2013; Bedder, 2015), environmental and social risks of exporting countries (Althaf & Babbitt, 2021), and recyclability and availability of materials (Achzet & Helbig, 2013).

In contrast to the current literature, we adopt the HHI index to measure the market power of the leading country in the international REE market as a prerequisite for investigating the costs of fringe oligopoly. As a commonly used measure of market concentration, it is calculated as the sum of the squares of market share percentages, expressed as:

$$HHI_{REEs} = \sum_{i=1}^{n} (q_i 100)^2 \tag{4}$$

where q_i is the proportion of global REEs held by country i. The HHI_{REEs} ranges from 0 (perfectly equal distribution) to 10,000 (monopoly, where one country holds 100 % of the REEs reserves). A higher HHI_{REEs} value indicates greater inequality and market concentration of REEs. Using the data reported in Tables 1 and 2 in the above section, and limiting the calculation at the first ten countries, we get that concentration index for commercialization is $HHI_{REEs} = 5002{,}10$ while the endowment of REEs is $HHI_{REEs} = 3067{,}01$. These results suggest that REEs endowments are highly concentrated, meaning that few countries control the international REEs market. In the sample used, markets are far from perfect competition, with the highest level of REEs concentration found in the market where REEs derivatives are traded.

3.4. Other control variables

To account for socio-economic values, we add: i) net investment cash flow (*ninv_cash_flow*), which includes foreign direct investment, portfolio investment, and domestic capital formation, crucial for expanding a country's productive capacity. According to the Solow-Swan growth model (1956), higher net investment cash flow increases capital stock, leading to higher GDP growth through productivity improvements; ii) mineral depletion rate (*mdr*), which is the ratio of the value of the stock of mineral resources, such as tin, gold, lead, zinc, iron, copper, nickel, silver, bauxite, and phosphate, to the remaining reserve lifetime (capped at 25 years). According to Capellán-Pérez et al. (2014), the mineral depletion rate can serve as a proxy for how efficiently a country manages its resources, as higher depletion rates without reinvestment may negatively affect GDP growth. Thus, high depletion without reinvestment in alternative sectors could lead to long-term stagnation. Additionally, iii) the fossil fuel energy consumption rate (*ffec*), which is the ratio of the stock of fossil fuel resources comprising coal, oil, petroleum, and natural gases essential to production processes and products, is also considered. As reported by Baz et al. (2021), fossil fuel energy is a significant indicator of economic and social development for any country. It is a major input to improve a country's economy, acting as a catalyst in industrial, transportation, agriculture, and other economic activities.

To account for innovation-related values, we add: i) the research and development expenditures as a percentage of GDP (*RDexp*), which includes both capital and current expenditures in basic research, applied research, and experimental development. According to Romer's Endogenous Growth Theory (1990), R&D drives technological progress, boosting Total Factor Productivity (TFP) and leading to sustained economic growth; ii) education (*school*), which comprises the adjusted net enrollment of school-age pupils for primary education, enrolled in either primary or secondary education, as a percentage of the total population in that age group. In line with Solow (1956), Mincer, 1974, Nelson and Phelps (1966), Romer, 1986; Romer, 1990, and Mankiw et al. (1992), education enhances labor productivity and innovation, which are key drivers of GDP growth. Besides, as indicated by Klinger (2018), an educated workforce can better utilize natural resources, such as REEs, in high-value industries like technology and advance high-tech manufacturing; additionally, iii) patent applications (*patents_noresp*) include the proportion of worldwide non-resident patent applications over the total number of patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office. By controlling patent applications, we can separate the effects of resource endowments from those of technological advancement on GDP growth rates. Countries with high patent activity develop REEs-based industries, such as electronics and the high-tech advanced manufacturing industry (Klinger, 2018).

For quality-related factors, we add: i) corruption (*corruption*) as a proxy for institutional quality. This perception-based index captures information on how public power is used for private gain, including petty and grand forms of corruption. This value controls for rent-seeking practices, poor quality of government, and misallocation of funds that potentially lead to uncertainty, discouraging investments in high-tech industries that depend on REEs (Zhan, 2017); ii) political stability (*political stability*) is a perception-based index related to the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically motivated violence and terrorism. This indicator ranges from −2.5 (weak) to 2.5 (strong). As indicated by Kamenopoulos and Agioutantis, stable governments are necessary to support investments in environmentally sound REEs production and trade.

Finally, the model controls for country and year effects to mitigate the potential issue of omitted variable bias. This is crucial because there might be other significant factors not captured by the variables included in the model—factors that could be unobservable due to data limitations or overlooked by the researcher and thus excluded from the model. The decision to add these controls is twofold. Firstly, other unobserved but potentially influential factors shaping REEs utilization are likely to have a territorial impact. This encompasses cultural variations and differences in human, social, and infrastructural factors, extending beyond what is considered by existing controls in the equation — specifically, the employment rate, income per capita, quality of life, and indicators for the availability of transport infrastructures to facilitate trade (such as motorways, highways, ports, airports, and railways). Secondly, this choice is consistent with avoiding the issue of overfitting. This risk involves the variable of interest lacking sufficient within-variability, making it undetectable in the estimates once the between-variability has been entirely absorbed by the fixed effects controls.

4. Model specification

Given the potential heterogeneity of the effects of REEs' endowment inequality at different levels of economic growth across countries worldwide, quantile regression is adopted as the primary estimation technique. As pointed out by Hau et al. (2022), unlike Ordinary Least Squares (OLS), which estimates the conditional mean effect of REEs endowment inequality on GDP growth rate, quantile regression provides a more comprehensive view by estimating the effects at different points of the growth distribution. This is particularly useful because countries with low, median, and high growth rates may respond differently to REEs' endowment inequality. Resource-dependent economies may suffer from the adverse effects of REEs' non-equal distribution compared to those that are not resource-dependent.

The analysis is performed using the quantile regression model developed by Koenker and Bassett, which uses multiple quantiles (τ = 0.10, 0.25, 0.50, 0.75, 0.90) to capture the heterogeneous effects of REEs endowments on the economic performance of countries worldwide, and minimizes the following asymmetric loss function:

$$\sum_{i=1}^{n} \rho_\tau (Y_{it} - X_i \beta^\tau) \tag{1'}$$

where $\rho_\tau(v) = v(\tau - I(v < 0))$ is the quantile loss function. Unlike OLS, the quantile regression allows us to observe how the effect changes across different segments of the GDP growth distribution by analyzing different quantiles separately (Hau et al., 2022). Thus, Eq. (1) is turned into a quantile econometric model (Gould & Rogers, 1994; Gould, 1992) as follows:

$$Q_\tau(Y_{it}) = \beta_0^\tau + \beta_1^\tau I_{REEs} + \beta_k^\tau \boldsymbol{X}_{it} + \alpha_i^\tau + \delta_t^\tau + \epsilon_{it}^\tau \tag{2'}$$

where $Q_\tau(Y_i)$ represents the quantile τ of the GDP growth rate ($GDPGR_{it}$) of country i at time t and the conditional quantile τ of the GDPPC growth rate ($GDPPCGR_{it}$) of country i at time t. The coefficient β_1^τ of I_{REEs} captures the heterogeneous effects of distribution of REEs endowments on the economic performance of country i at time t. Then, the coefficient β_k^τ refer to the vector $\boldsymbol{X}_{it}$ which includes economic factors (such as net investment cash flows, mineral depletion rate, and fossil fuel energy consumption), innovation-related indicators (including R&D expenditures, education, and patent applications), and institutional quality variables (such as levels of corruption and political stability). Finally, the coefficient α_i^τ represents country-specific fixed effects, while δ_t^{τ} accounts for the time-specific effects. In contrast, ϵ_{it}^{τ} is the error term that accounts for factors that affect the GDP growth rate of a country but are not explicitly included in the model.

5. Results

5.1. Baseline quantile regression

We conduct a univariate quantile regression with bootstrapped standard errors to assess the heterogeneity of inequality distribution on a country's economic performance. As suggested by Koenker and Bassett, bootstrapping provides robust standard errors that account for complex error structures and non-normality. The dependent variables used are the GDP growth rate (*gdpgrowthr*) and the GDP per capita growth rate (*gdppc_growr*), as reported in Tables 3 and 4, respectively. Columns 1 and 2 report estimates for low quantiles (.10 and.25), column 3 presents estimate for the medium quantile (.50), and columns 4 and 5 indicate estimates for high quantiles (.75 and.90). Ideally, countries in the low quantiles denote those with low growth, in the middle quantiles those with neutral growth, and the high quantiles those with high growth rates. In both tables, country and year effects are included to control for territorial-related and time-related issues. At the bottom of each table, the total number of observations is reported.

In Table 3, the inequality index of REEs (I_{REEs}) has the expected negative sign in low (.10 and.25) and medium (.50) quantiles, while it exhibits a positive sign in the high (.90) quantile. In columns 2 and 3, the coefficients are statistically significant at the 5 % and 1 % significance levels (level, hereafter), respectively. On average, in the low quantile, a unit increase of I_{REEs} is associated with a 6.8 % decrease in the GDP growth rate, while in the medium quantile, a unit increase of I_{REEs} is associated with a 5.7 % decrease in the GDP growth rate, ceteris paribus.

Similarly, in Table 4, the I_{REEs} shows a negative sign from low to medium quantiles while retaining a positive sign in one high quantile only. In columns 1, 3, and 5, the coefficients are statistically significant at the 10 % and 1 % levels, respectively. On average, in the low quantile, a unit increase of I_{REEs} is associated with an 8.7 % decrease in the GDPPC growth rate, while in the medium quantile, a unit increase of I_{REEs} is associated with a 2.1 % decrease in the GDPPC growth rate, ceteris paribus.

In addition to the previous results, in the high quantile, on average, a unit increase of I_{REEs} is associated with a 4.3 % increase in the GDPPC growth rate, ceteris paribus.

Table 3
Univariate quantile regression with bootstrapped standard errors.

	(1)	(2)	(3)	(4)	(5)
Quantiles	.10	.25	.50	.75	.90
Dependent Variable	gdpgrowr	gdpgrowr	gdpgrowr	gdpgrowr	gdpgrowr
Inequality_REEs	-10.25	-6.802**	-5.658***	-1.498	0.113
	(8.341)	(3.100)	(1.340)	(3.145)	(2.203)
Constant	8.026*	10.98***	12.69***	12.43***	12.14***
	(4.481)	(2.134)	(1.226)	(1.847)	(1.110)
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	2578	2578	2578	2578	2578

Robust standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Table 4
Baseline quantile regression with bootstrapped standard errors.

	(1)	(2)	(3)	(4)	(5)
Quantiles	.10	.25	.50	.75	.90
Dependent Variable	gdppc_growr	gdppc_growr	gdppc_growr	gdppc_growr	gdppc_growr
Inequality_REEs	-8.711*	-4.053	-2.136***	-0.525	4.203***
	(4.878)	(3.326)	(0.816)	(4.020)	(1.064)
Constant	4.902	7.828***	9.217***	10.23***	8.805***
	(4.934)	(2.606)	(0.590)	(2.029)	(0.642)
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	2578	2578	2578	2578	2578

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Although preliminary, evidence suggests, as reported in Fig. 1, that the endowment of REEs, mainly concentrated in China, the US, and a few other countries, has heterogeneous effects on the growth rates of countries located in low, medium, and high quantiles. This, in turn, influences their economic performance differently. However, as other key variables omitted here may explain variability in each country's economic performance, additional regressions are conducted virgo as demonstrated by Fig. 2 below.

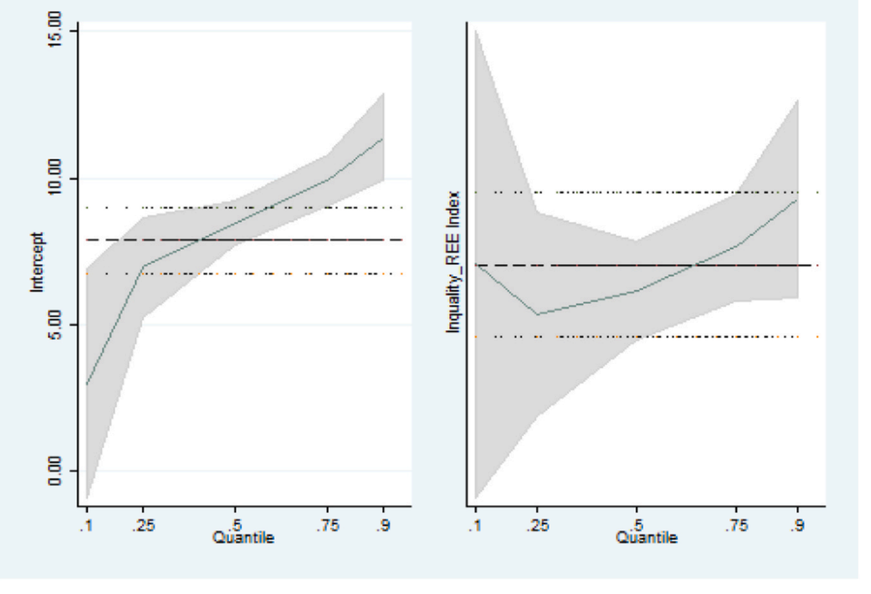

Fig. 2. Inequality Index – Univariate Quantile Regression Analysis. Source: Authors' elaboration on STATA estimations. Note: the x-axis represents different **quantiles** (e.g., 10th, 25th, 50th, 75th, 90th percentiles). The y-axis represents the **coefficient estimates** for the independent variable. On the left, it represented the Intercept, while on the right there is represented the *Inequality_REEs* is represented. The solid line shows how the estimated coefficient changes across different quantiles, while the shaded region represents the **confidence intervals**, indicating statistical uncertainty around the estimates.

Table 5
Multivariate quantile regression with bootstrapped standard errors – *gdp_growthr*.

	(1)	(2)	(3)	(4)	(5)
Quantiles	.10	.25	.50	.75	.90
Dependent Variable	gdpgrowthr	gdpgrowthr	gdpgrowthr	gdpgrowthr	gdpgrowthr
Inequality_REEs	-1.366	-0.5845	-1.555*	1.858***	2.375***
	(1.237)	(0.941)	(0.821)	(0.691)	(0.766)
inv_cash_flow	0.080*	0.091*	0.002	-0.026	-0.015
	(0.042)	(0.047)	(0.043)	(0.032)	(0.037)
mdr	0.177	0.214	0.010	0.093	0.320
	(0.383)	(0.543)	(0.444)	(0.456)	(0.418)
ffec	-0.015	-0.024	-0.022	-0.029	-0.041
	(0.058)	(0.039)	(0.032)	(0.048)	(0.045)
RDexp	-0.759	0.123	0.227	-0.425	-0.547
	(0.803)	(0.716)	(0.693)	(0.594)	(0.810)
school	0.108	0.095	0.062	0.089	0.158
	(0.108)	(0.073)	(0.098)	(0.069)	(0.09)
patent_nores_p	2.347**	0.844	0.784	0.278	-0.0121
	(1.015)	(1.265)	(1.185)	(1.090)	(1.033)
corruption	-0.0108	-0.0201	-0.0636	-0.0670*	-0.0834**
	(0.032)	(0.043)	(0.042)	(0.036)	(0.042)
political stability	1.729	1.787*	1.390**	0.466	1.348
	(1.393)	(1.079)	(0.690)	(0.700)	(0.826)
Constant	121.7	51.08	-157.7*	-186.3***	-242.7***
	(119.1)	(93.66)	(82.24)	(68.98)	(80.71)
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	2578	2578	2578	2578	2578

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.2. Multivariate quantile regression

We conduct a multivariate regression with bootstrapped standard errors to assess the consistency of our prior results. The dependent variables used are the GDP growth rate (*gdpgrowthr*) and the GDP per capita growth rate (*gdppc_growthr*), as reported in Tables 5 and 6, respectively. Columns 1 and 2 report estimates for low quantiles (.10 and.25), column 3 presents estimate for the medium quantile (.50), and columns 4 and 5 indicate estimates for high quantiles (.75 and.90). Estimates of both tables include control variables to account for economic, socio-cultural, and quality-related issues. Country and year effects are included in all models to account for territorial and time variations. At the bottom of each table, the total number of observations is reported.

In Table 5, the I_{REEs} maintains its expected negative sign in the low (.10 and.25) and medium (.50) quantiles, while it exhibits a positive sign in the high (.75 and.90) quantiles. Although the coefficients lose their statistical significance in low quantiles, they are statistically significant at 10 % level in the medium (.50) quantile, and 1 % level in the high (.75 and.90) quantiles, respectively. On average, a unit increase of I_{REEs} is associated with a 1.56 % decrease in the GDP growth rate in the medium (.50) quantile, ceteris paribus. In contrast, a unit increase of I_{REEs} is associated with a 1.86 % and a 2.38 % increase in the GDP growth rate in the high (.75 and.90) quantiles, ceteris paribus.

Table 6
Multivariate quantile regression with bootstrapped standard errors – *gdppc_growthr*.

	(1)	(2)	(3)	(4)	(5)
Quantiles	.10	.25	.50	.75	.90
Dependent variable	gdppc_growthr	gdppc_growthr	gdppc_growthr	gdppc_growthr	gdppc_growthr
Inequality_REEs	-1.507	-4.812	-1.243	1.803*	1.981*
	(1.153)	(0.957)	(0.823)	(0.970)	(1.184)
inv_cash_flow	0.071	0.094	0.047	-0.027	-0.025
	(0.045)	(0.062)	(0.037)	(0.045)	(0.049)
mdr	0.122	0.0925	0.0449	-0.268	-0.464**
	(0.363)	(0.362)	(0.529)	(0.480)	(0.223)
ffec	-0.013	-0.024	-0.056	-0.006	-0.049
	(0.071)	(0.037)	(0.049)	(0.037)	(0.051)
RDexp	-0.728	-0.080	0.011	-0.430	-0.777
	(0.724)	(0.852)	(0.701)	(0.846)	(1.263)
school	0.133*	0.121	0.064	0.084	0.122
	(0.069)	(0.084)	(0.076)	(0.104)	(0.079)
patent_nores_p	1.724*	1.296**	0.986	-0.160	-0.292
	(1.024)	(0.623)	(1.100)	(0.909)	(1.236)
corruption	-0.002	-0.005	0.048	-0.068	-0.076
	(0.028)	(0.037)	(0.047)	(0.052)	(0.057)
political stability	1.867*	1.743*	1.702**	0.544	0.852
	(1.078)	(0.895)	(0.807)	(0.607)	(0.780)
Constant	131.6	36.63	-124.3	-183.3*	-200.1*
	(112.2)	(94.32)	(80.31)	(97.22)	(116.0)
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	2578	2578	2578	2578	2578

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To control for socio-economic factors, we add: i) The variable *inv_cash_flow*, which has a positive sign in the low (.10 and.25) and medium (.50) quantiles but a negative sign in the high (.75 and.90) quantiles. It is statistically significant at the 10 % level in the low quantiles only; ii) The variable *mdr*, which has a positive sign in the low (.10 and.25) and medium (.50) quantiles but a negative sign in the high (.75 and.90) quantiles. It is statistically significant at the 5 % level in the high quantile only; iii) the variable *ffec* maintains a negative sign in all quantiles but is not statistically significant.

To control for innovation-related factors we insert: i) the variable *RDexp*, which has a negative sign in all quantiles, but its coefficient is not statistically significant; ii) the variable *school*, which has a positive sign in all quantiles, but it is statistically significant at the 10 % level only in the low quantile; iii) the variable *patent_nores_p*, which shows the expected positive sign in all quantiles but is seldom significant, specifically at 5 % level in the low (.10) quantile.

To control for quality-related factors, we add: i) the variable of *corruption*, which has the expected negative sign in all quantiles but is statistically significant at 10 % level in the high (.75 and.90) quantiles only; ii) the variable of *political stability*, which maintains the expected positive sign in all quantiles but is statistically significant at 10 % level in the low (.10 and.25) quantiles and at 5 % level in the medium (.50) quantile.

In Table 6, the I_{REEs} retains its expected negative sign in the low (.10 and.25) and medium (.50) quantiles, while it exhibits a positive sign in the high (.75 and.90) quantiles. Although the coefficients lose their statistical significance in the low (.10 and.25) and medium (.50) quantiles, they maintain their statistical significance at the 10 % level in high (.75 and.90) quantiles. On average, a unit increase of I_{REEs} is associated with a 1.80 % and 1.98 % increase in the GDP per capita growth rate in high (.75 and.90) quantiles, respectively. The slight variation in the coefficient of I_{REEs} (+0.06 % and +0.38 %) in the high quantiles demonstrates that the index corroborates consistent estimates, regardless of which of the two dependent variables is used.

Similar to the estimates reported in Table 6 we add the same control variables to account for socio-economic, innovation, quality-related factors, as well as country and year effects. Although some of these variables lose their statistical significance, the signs are preserved, confirming the robustness of the estimates.

To sum up, by adding control variables, our findings confirm that countries in low and medium quantiles suffer more from the misallocation of REEs compared to countries in high quantiles. This is due to their varying levels of innovation, education, expenditure on R&D, government quality, and political stability, which, in turn, influence their supply chain and industrial policies (Golroudbary et al., 2022).

5.3. The costs of oligopoly with fringe

A sustained and guaranteed supply of REEs is imperative for developing a country's national security to support its manufacturing, defense, and high-tech industries. Despite the term "rare", REEs are not rare; however, their production has been dominated by China, primarily due to low prices resulting from cheap labor and a lack of environmental compliance (Pan et al., 2021; Salim et al., 2022). Although abundant REEs deposits exist in many parts of the world, including Australia, Brazil, India, Russia, the United States, and Vietnam, China remains the dominant REEs supplier and attempts to control the entire value chain by encouraging its major multinational companies to build their manufacturing facilities, facilitated by a lack of legal compliance (He, 2018; Salim et al., 2022).

Hence, China and the aforementioned countries act as oligopolists in the REEs market (Lai et al., 2024). China has a disproportionately large share of global REEs, which can influence market outcomes, including pricing and availability, to the detriment of fringe countries. According to Masson and Shaanan's, the cost of an oligopoly with a fringe arises when the dominant supplier, like China, exerts significant market power over smaller, less influential competitors. The dominant supplier's ability to set higher prices or restrict supply can impose additional costs on downstream industries and importing nations, effectively altering the competitive equilibrium. This cost is not solely a reflection of production expenses but also encompasses the strategic use of market power, which can lead to inefficiencies and reduced global economic performance. Adapting Masson and Shaanan's theory to the context of REEs, this study further analyzes the degree of association between the oligopolistic costs imposed by China and a few other countries, and the economic growth of countries worldwide. Thus, the econometric model theorized by Equation 1 assumes the following form:

$$Q_\tau(Y_{it}) = \beta_0^\tau + \beta_1^\tau I_{REEs} + \beta_2^\tau Oligopoly\_cost_{it} + \beta_3^\tau \ln gdppc_{it} + \beta_4^\tau Oligopoly\_cost_{it} {*} \ln gdppc_{it} + \beta_k^\tau \boldsymbol{X} + \alpha_i^\tau + \delta_t^\tau + \epsilon_{it}^\tau \tag{3'}$$

where $Q_\tau(Y_i)$ represents the quantile τ of the GDP growth rate ($GDPGR_{it}$) of country i at time t and the conditional quantile τ of the GDPPC growth rate ($GDPPCGR_{it}$) of country i at time t. Then, the coefficient β_2^τ captures the effects of the cost of oligopoly that is expressed as: $Oligopoly\_cost_{it} = \frac{REEs\ trade\ from\ the\ dominant\ suppliers}{Total\ REEs\ trade\ value\ worldwide}$; the coefficient β_3^τ captures the effects of the natural logarithm of Gross Domestic Product *per capita* ($\ln gdppc_{it}$) of country i at time t, added as proxy of country's level economic development; the coefficient β_4^τ catches the effects of the interaction term between GDP *per capita* and oligopoly cost of country i at time t to assess if the effect of market power on growth is moderated by a country's development level—revealing, for example, whether richer economies can better mitigate the negative consequences of oligopolistic pricing strategies. The not-mentioned coefficients describe the effects of the variables already presented in the *Model Specification*. Finally, α_i^τcaptures the country-specific effects, whereas δ_t^τ indicates the time-specific effects; ϵ_{it}^τ is the error term that accounts for factors that are not included in the model.

Estimates from Equation 3 are reported in the following Table 7. The dependent variables used are always (*gdpgrowthr*) and (*gdppc_growthr*). Columns from 1 to 4 report estimates in low quantiles (.10 and.25), columns 5 and 6 present estimates in medium quantile (.50), and columns from 7 to 10 indicate estimates in the high quantiles (.75 and.90). All estimates include control variables of socio-economic, innovation, and quality-related issues. Country and year effects are reported in all models to account for territorial and time effects. At the bottom, the total number of observations is reported.

By considering *gdpgrowthr* as dependent variable, the coefficient for I_{REEs} retains its expected negative sign in the low (.10 and.25) and medium (.50) quantiles, while it exhibits a positive sign in the high (.90) quantile. The coefficients are statistically significant at the 1 % level in the low (.10 and.25) and medium (.50) quantiles, only. On average, a unit increase in I_{REEs} is associated with a 15.77 % and 9.77 % decrease in the economic performance in the low (.10 and.25), and a 5.92 % decrease in the medium (.50) quantiles. Similarly, considering *gdppc_growthr*, the coefficient for I_{REEs} retains its expected negative sign in the low (.10 and.25) and high (.75) quantiles, while it exhibits a positive sign in the high (.90) quantile. The coefficients are statistically significant at the 1 % and 10 % levels in the low (.10 and.25) and high (.75) quantiles. On average, a unit increase in I_{REEs} is associated with a 17.26 % and 7.13 % decrease in the economic performance in the low (.10 and.25), and a 3.10 % and 3.93 % decrease in the high (.75 and.90) quantiles, ceteris paribus.

By considering *gdpgrowthr* as the dependent variable, the coefficient for *oligopoly_cost* shows the expected negative sign in all quantiles and is statistically significant at 1 %, 5 %, and 10 % in the low (.10 and.25) and high (.75) quantiles, respectively. On average, a unit increase in *oligopoly_cost* is associated with a 16.48 % and 11.57 % decrease in the economic performance of countries in the low quantiles, while it is associated with an 11.28 % decrease in the economic performance of countries in the high quantile. Similarly, considering *gdppc_growthr* as the dependent variable, the coefficient for *oligopoly_cost* maintains its expected negative sign across all quantiles and is statistically significant at 1 %, 5 %, and 10 % in the low (.10 and.25), medium (.50), and high (.75) quantiles, respectively. On average, a unit increase in *oligopoly_cost* is associated with a 25.10 % and 15 % decrease in the economic performance of countries in the low quantiles, a 17.52 % decrease in the medium quantile, and decreases of 15.88 % and 14.89 % in the high quantiles, ceteris paribus.

By considering *gdpgrowthr* as the dependent variable, the coefficient for *lngdppc* has a positive sign in all specifications and is statistically significant at 1 % in the low (.10 and.25)

Table 7
Estimated results with the oligopoly cost and the interaction term.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quantiles	.10	.10	.25	.25	.50	.50	.75	.75	.90	.90
Dependent Variable	gdpgrowthr	gdppc_growr	gdpgrowthr	gdppc_growr	gdpgrowthr	gdppc_growr	gdpgrowthr	gdppc_growr	gdpgrowthr	gdppc_growr
Inequality_REEs	-15.771***	-17.26***	-9.769***	-7.132*	-5.919***	-0.644	-1.220	-3.107***	0.0300	3.928**
	(0.791)	(1.438)	(1.644)	(3.789)	(0.704)	(4.147)	(2.964)	(0.886)	(1.759)	(1.720)
oligopoly_cost	-16.481***	-25.10***	-11.571**	-15.99**	-8.195	-17.52*	-11.281*	-15.88***	-7.696	-14.89***
	(4.444)	-8.783	(4.866)	(7.868)	(5.440)	(9.049)	(6.162)	(5.287)	(5.530)	-4.613
lngdppc	4.230***	4.297***	1.677***	1.391***	0.387	0.0183	0.431***	0.401	0.153	0.616*
	(0.551)	(0.650)	(0.425)	(0.485)	(0.287)	(0.277)	(0.150)	(0.247)	(0.290)	(0.315)
oligopoly_cost*lngdppc	-2.794***	-2.467***	-1.037**	-0.647*	-0.311	0.190	0.0607	-0.0808	-0.947**	-0.883
	(0.394)	(0.506)	(0.414)	(0.357)	(0.511)	(0.311)	(0.217)	(0.418)	(0.379)	(0.773)
Constant	-15.15***	-16.62***	0.937	-0.00101	10.15***	10.44***	15.13***	7.135***	13.24***	4.464*
	(3.724)	(4.085)	(3.223)	(3.941)	(1.855)	(2.648)	(1.911)	(1.613)	(2.011)	(2.531)
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2578	2578	2578	2578	2578	2578	2578	2578	2578	2578

Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

and high (.75) quantiles. On average, a unit increase in *lngdppc* is positively associated with a 4.23 and 1.67 increase in the economic performance of countries in the low (.10 and.25) quantiles, and a 0.43 increase in the economic performance of countries in the high (.75) quantile. Considering *gdppc_growthr* as the dependent variable, the coefficient for *lngdppc* has a positive sign in all specifications and is statistically significant at 1 % in the low (.10 and.25) and high (.75) quantiles. On average, a unit increase in *lngdppc* is positively associated with an increase of 4.29 and 1.39 in the economic performance of countries in the low (.10 and.25) quantiles, and an increase of 0.62 in the high (.75) quantile, ceteris paribus. According to Solow's growth theory (1956), countries in the lower quantiles tend to grow faster due to the catch-up effect, whereas countries in the medium and high quantiles grow at a moderate pace since they are already developed with better infrastructures.

Considering *gdpgrowthr* as the dependent variable, the coefficient for the interaction term oligopoly_cost*lngdppc predominantly has a negative sign and is statistically significant at 1 % and 5 % in low (.10 and.25) and high (.75) quantiles. On average, a unit increase in the combined effects of income level and oligopoly costs for REEs is associated with a decrease of 2.80 % and 1.04 % in the economic performance of countries in low quantiles (.10 and.25), and a decrease of 0.95 % in the high quantile (.90), ceteris paribus. Considering *gdppc_growthr* as the dependent variable, the coefficient for oligopoly_cost*lngdppc is negative and statistically significant at 1 % and 10 % in the low (.10 and.25) quantiles only. On average, a unit increase in the combined effects of a country's income level and oligopoly costs for REEs is associated with a decrease of 2.47 % and 0.67 % in the economic performance of countries in low quantiles (.10 and.25), ceteris paribus.

5.4. Robustness check

To check the consistency of our estimates, we ran both univariate and multivariate regressions with the Herfindahl-Hirschman Index (*HHI_index* hereafter) in place of our new index for inequality of REEs distribution. The HHI index is popularly used in this research area to identify geopolitical risk of REEs supplies (Althaf & Babbitt, 2021; Goe & Gaustad, 2014; Santillán-Saldivar et al., 2021). Tables B.1 and B.2 in Appendix B present univariate and multivariate regression analyses with *gdpgrowthr* as the dependent variable, while Tables B.3 and B.4 show the univariate and multivariate regression analyses with *gdppc_growthr* as the dependent variable. In both tables, columns 1 and 2 report estimates for low quantiles (.10 and.25), column 3 presents the estimate for the medium quantile (.50), and columns 4 and 5 indicate estimates for high quantiles (.75 and.90). Country and year effects are included in all models. The number of observations is reported at the bottom of each table.

In Table B.1, the *HHI_index* maintains its expected negative sign in the low (.10 and.25) and medium (.50) quantiles, while it exhibits a positive sign in the high (.75 and.90) quantiles. The coefficients maintain their statistical significance at the 1 % level in low (.10 and 25) and medium (.50) quantiles only. Similar to the estimates presented in Table 3 of the previous section, on average, a unit increase in the *HHI_index* is associated with a 5.13 % and 3.40 % decrease in the GDP growth rate in low (.10 and.25) quantiles and medium (.50) quantile, ceteris paribus.

In Table B.2, the *HHI_index* maintains its expected negative sign in the low (.10 and.25) and medium (.50) quantiles, while it exhibits a positive sign in the high (.75 and.90) quantiles. The coefficients are statistically significant at 10 % in the low (.10), at 1 % in medium (.50), and high (.75) quantiles. Similar to the estimates presented in Table 4 of the previous section, on average, a unit increase in the *HHI_index* is associated with 4.37 % and 1.25 % decrease in the GDPPC growth rate in low (.10) and medium (.50) quantiles, whereas is associated with 2.11 % increase in GDPPC growth rate in the high (.90) quantile, ceteris paribus.

In Table B.3, the *HHI_index* maintains its expected negative sign in the low (.10 and.25) and in medium (.50) quantiles, while it exhibits a positive sign in the high (.75 and.90) quantiles. The coefficients are statistically significant at 1 % in high (.75 and.90) quantiles only. Similar to the estimates presented in Table 5 on average, a unit increase in the *HHI_index* is associated with a 7.59 % and 9.69 % increase in the GDP growth rate in the high (.75 and.90) quantiles.

In Table B.4, the *HHI_index* upholds its expected negative sign in the low (.10 and.25) and in medium (.50) quantiles, while it preserves a positive sign in the high (.75 and.90) quantiles. The coefficients are statistically significant at 10 % in the low (.10) and in medium (.50) quantiles, whereas in the high (.75 and.90) quantiles are statistically meaningful at 5 % and 10 % respectively. Like the estimates presented in Table 6 of the previous section, on average, a unit increase in the *HHI_index* is associated with a 6.15 % and 5 % decrease in the GDPPC growth rate in the low (.10) and medium (.50) quantiles, respectively. In contrast, a unit increase in the *HHI_index* is associated with a 7.36 % and 8.08 % increase in GDPPC growth rate in the high (.75 and.90) quantiles, respectively, ceteris paribus.

For the remaining socio-economic, innovation, and quality-related variables, although some lose their statistical significance, the signs are preserved, confirming the robustness of the previously presented results.

5.5. Additional analyses for robustness check

To further assess the robustness of the estimated results, this section presents additional robustness checks. We conduct an Instrumental Variable (IV) quantile regression to mitigate endogeneity bias. The results are reported in Table B.5 of Appendix B. The instrument used to control the validity of the newly built index is land under cereal production (*landcer*), which refers to the harvested area for cereals, including wheat, rice, maize, barley, oats, rye, millet, sorghum, buckwheat, and mixed grains. The idea of using land as an instrument relies on the fact that: i) cereal production depends on land availability and agricultural suitability, which are influenced by natural resource endowment. Hence, territories with arable land have different priorities in terms of resource extraction than those rich in mineral resources like REEs; ii) cereal production does not directly affect GDP growth rate except through its correlation with REEs endowment inequality. Since these two conditions are satisfied (relevance and exogeneity, respectively), *landcer* is a valid instrument.[2]

In Table B.5, columns denoted with *a* report the *gdpgrowthrate* while columns denoted with *b* report the *gdpppc_growthrate* as dependent variables. Besides, columns 1 and 2 present estimates for low quantiles (.10 and.25), column 3 for the medium quantile (.50), and columns 4 and 5 for high quantiles (.75 and.90). The other control variables, country and year effects are included in all models. The number of observations is reported at the bottom of the table.

In all specifications, I_{REEs} maintains its expected negative sign in all quantiles. The coefficients are statistically significant at 1 % in low (.10 and.25), medium (.50) and high (.75 and.90)

[2] In STATA, to check instrument relevance and exogeneity, we perform the first stage IV regression. The F-statistic (14.22) > 10 confirms the validity of the instrument adopted. Then, the Hansen J-test with a p-value (0.13) > 0.05 confirms that the instrument does not correlate with the error term.

quantiles. Similar to the main estimates, on average, a unit increase in the I_{REEs} is associated with a decrease between 7.78 % and 6.08 % on the *gdpgrowthr* and a decrease between 6.6 % and 5.04 % on the *gdppc_growthr* of countries in low quantiles, with a decrease of 6.19 % on the *gdpgrowthr* and a decrease of 6.15 % on the *gdppc_growthr* of countries in medium quantiles, with a decrease between 5.53 % and 4.788 % on the *gdpgrowthr* and a decrease between 3 % and 1.76 % on the *gdppc_growthr* of countries in high quantiles, ceteris paribus.

In Table B.6, instead, a dummy variable denoting developing countries of the sample (*D_developing*) and its interaction term with the index are added.

In all specifications, I_{REEs} maintains its expected negative sign all quantiles. The coefficients are statistically significant at 1 % in low (.10 and.25), medium (.50), and high (.75 and.90) quantiles. On average, a unit increase in the I_{REEs} is associated with a decrease between 9.53 % and 8.89 % on the *gdpgrowthr* and a decrease between 6.94 % and 6.47 % on the *gdppc_growthr* of countries in low quantiles, with a decrease of 7.87 % on the *gdpgrowthr* and a decrease of 6.43 % on the *gdppc_growthr* of countries in medium quantiles, with a decrease between 6.06 % and 4.60 % on the *gdpgrowthr* and a decrease between 4.72 % and 2.27 % on the *gdppc_growthr* of countries in high quantiles, ceteris paribus.

The coefficient denoting the *developing* countries has the expected negative sign and is statistically significant at 10 %, 5 %, and 1 % in low (.10 and.25), medium (.50) and high (.75 and.90) quantiles. On average, the developing countries grow less than developed countries, ceteris paribus.

The coefficient for the interaction (*Inequality*D_developing*) is included to evaluate how the effects of REEs inequality differ between developing and developed countries. The coefficient is negative and statistically significant at 1 % and 5 % in low (.10 and.25), medium (.50), and high (.75 and.90) quantiles. The negative sign indicates that the effects of REEs inequality are greater in developing countries than in developed countries. Specifically, in the low quantile (.25), the additional negative effect is larger (-13 %) compared to (-11 %) in the medium (.50) and (-8 %) in the high (.75) quantile, indicating that low growth developing economies are more vulnerable to REEs inequality. The following section will discuss the above results in more detail.

5.6. Endogeneity

To address the dynamic nature of GDP growth and potential endogeneity between growth and REEs-related inequality, we adopt the one-step system of Generalized Methods of Moments (GMM) estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). This approach allows for consistent estimation in the presence of endogenous regressors and unobserved country and time-specific effects, as follows:

$$Y_{it} = \beta_0 Y_{it-1} + \beta_1 I_{REEs} + \beta_k \boldsymbol{X}_{it} + \alpha_i + \delta_t + \varepsilon_{it} \tag{4'}$$

where Y_{it} is the dependent variable (*gdpgrowthr* or *gdppc_growr*). Then, β_0 refers to the one-year lagged term of the dependent variable, β_1 denotes the *Inequality_REEs*, while β_k is for vectors of control variables. Finally, α_i indicates the country-specific effects, δ_t to the year-specific effects, and ε_{it} is the idiosyncratic error term. The estimated coefficient from equation 4 are reported in Table B.7 of Appendix B.

Tables 8 and 9 present the estimated coefficients of *Inequality_REEs* across different quantiles in the quantile regression model, compared with the average structural effect estimated using the one-step SGMM.

Table 8
Comparison of quantile regression and system GMM results – Dependent variable: gdpgrowthr.

Quantile	Coeff. IREEs	Std. Error	Interpretation
0.10	-1.366	1.237	Weakly negative effect in low-growth economies
0.25	-0.5845	0.941	Weakly negative in lower-middle growth economies
0.50	-1.555*	0.821	Moderate, significant negative in upper mid-growth economies
0.75	1.858***	0.691	Moderate, significant positive in middle-growth economies
0.90	2.375***	0.766	Strong, highly significant positive in high-growth economies
SGMM	-2.611**	1.080	Average negative effect, accounting for endogeneity

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Source: authors' elaboration on estimated results

Table 9
Comparison of quantile regression and system GMM results – Dependent variable: gdppc_growr.

Quantile	Coeff. IREEs	Std. Error	Interpretation
0.10	-1.507	1.153	Weakly negative effect in low-growth economies
0.25	-4.812	0.957	Weakly negative in lower-middle growth economies
0.50	-1.243	0.823	Weakly negative in upper mid-growth economies
0.75	1.803*	0.970	Moderate, significant positive in middle-growth economies
0.90	1.981*	1.184	Strong, highly significant positive in high-growth economies
SGMM	-2.567**	1.020	Average negative effect, accounting for endogeneity

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Source: authors' elaboration on estimated results

The results presented in both tables reveal a heterogeneous relationship between REEs-related inequality and economic growth—measured by both the GDP growth rate and per capita GDP growth rate—across different stages of economic performance. The quantile regression estimates indicate that REEs inequality exerts a weakly negative influence on growth in low-growth and lower-middle-growth economies, though these effects are statistically insignificant. At the median (50th percentile), the negative association becomes moderately strong and statistically significant, suggesting that inequality in this context may hinder economic performance. On the other hand, at higher quantiles—specifically the 75th and 90th percentiles—REEs inequality exhibits a statistically significant and positive effect on growth. This pattern implies that in higher-growth economies, inequality in the REEs sector may be associated with capital concentration, targeted investment, or structural transformation that supports productivity gains.

By contrast, SGMM results indicate a statistically significant average negative effect of REEs inequality on both GDP and GDP per capita growth (with coefficients of –2.61 and –2.57, respectively). These findings suggest that, despite positive effects in higher-growth contexts, REEs-related inequality is, on average, detrimental to long-term economic growth. This may reflect underlying issues such as rent-seeking behavior, institutional weaknesses, or inequitable distribution of resource rents.

Overall, the evidence highlights the need for differentiated policy responses that consider a country's stage of development and institutional capacity to manage natural resource wealth effectively.

6. Discussion

Since the 1960s, REEs have gained prominence with the advent of television screens and early computer systems. In recent decades, their applications have extended beyond traditional sectors like metallurgy and chemical industries, playing an increasingly significant role in the production of advanced high-technology products (Wang et al., 2020). Nowadays, the significance of REEs on the global stage is steadily increasing as their strategic importance becomes more evident. REEs, as non-renewable strategic minerals, play a crucial role in producing many high-tech and environmentally friendly technologies. For example, permanent magnets account for 30 % of REEs demand, the highest in weight and value (Salim et al., 2022; Wang et al., 2020). REEs are also crucial in military applications, such as targeting and weapon systems, guidance, and control (Proelss et al., 2018). However, due to the lack of substitutes for REEs and their strategic importance to a nation's economy and defense issues, the demand for REEs is generally inelastic (Proelss et al., 2018). Moreover, the supply of REEs is unevenly distributed, giving high bargaining power to the controllers of the REEs market in shaping global political and economic equilibrium (Mancheri et al., 2019; Proelss et al., 2018). Although rare earth mining activities outside of China have been developed, China is still the primary producer of certain REEs with the largest reserve share of 44 % in 2023, according to the US Geological Service Mineral Commodity Summaries 2023.[3] Other economies are taking concerted steps to enhance their access to and control over REEs, a trend closely tied to the implementation of policies with far-reaching implications. These elements play a pivotal role in two of the most pressing geopolitical challenges of our time: national defense and the transition towards sustainable green energy resources (Bonaime et al., 2018). Although some literature has focused on China's rare earth policies, particularly after the REEs export restriction incident in 2010 (Hayes-Labruto et al., 2013; Mancheri, 2015), few studies have evaluated the effects of REEs trade on Chinese policies, including environmental and resource taxation (Wan & Wen, 2017; Wang et al., 2020), industry integration and upgrade (Han et al., 2016; Rao, 2016), Chinese rare earth stockpiling (Brown & Eggert, 2018), the rare earth supply chain (Klossek et al., 2016), and REEs trade and geopolitical risk (Fan et al., 2023). According to our empirical results from the quantile regression analyses, we provide new evidence on the heterogeneous relationship between the unequal distribution of REEs and the economic performance of countries worldwide. Additionally, we estimated the economic costs of an oligopoly of REEs with a fringe worldwide, given the income level of each country. The results are remarkable and discussed as follows.

Firstly, assuming China and a few other countries (e.g., Australia, Brazil, India, Russia, US, Vietnam) as oligopolists in the REEs market, the relationship between REEs natural endowment and the economic performance is varying across countries located in the low (.10 and.25), medium (.50), and high (.75 and.90) quantiles. Specifically, there is a negative and significant relationship between REEs unequal endowment and economic performance for countries in the low and medium quantiles, while there is a positive and seldom significant relationship for countries in the high quantile. Our findings suggest that the effects of the unequal distribution of REEs are mainly suffered by developing (low quantiles) rather than developed (high quantiles) countries. This result can be explained through economic, geopolitical, and industrial factors such as: i) the natural resource distribution and the inability to exploit them, since many

[3] For more details see: Mineral commodity summaries 2023, DOI: 10.3133/mcs2023

developing countries have significant natural resource endowments but lack the proper technological infrastructure, capital, and expertise to use these resources effectively (Salim et al., 2022). In contrast, developed countries tend to have diversified economies with advanced industrial bases and technological capabilities, reducing their direct dependence on REEs extraction for economic growth; ii) the export-oriented trade policy, since many developing countries often rely on exporting raw REEs rather than processing and utilizing them for high-value manufacturing, as developed countries do. The reliance on raw material exports makes developing countries vulnerable to price volatility and trade dependencies, especially; iii) the lack of alternative circular economy strategies, as many developing countries are not committed to recycling to turn waste products into raw materials and use them as alternatives to REEs (Watari et al., 2019); iv) the lack of strong governmental policies and a poor level of education in developing countries, technology transfer, education, political stability, and economic diversification. This weak institutional framework prevents them from effectively leveraging REEs. In contrast, developed countries invest in research and innovation, reducing their vulnerability to REEs supply shocks by improving recycling technologies (Salim et al., 2022).

Secondly, assuming China and a few other countries as oligopolists in the REEs market, the relationship between the cost of oligopoly and economic performance varies in magnitude across countries placed in the low (.10 and.25), medium (.50), and high (.75 and.90) quantiles. In fact, there is a negative and significant relationship between oligopoly costs imposed by countries with natural REEs and the economic performance of other countries worldwide. Evidence suggests that, given the income level of each country, developing countries suffer more than developed ones from the oligopolistic behavior of China and a few other nations with REEs. This occurs because countries with low economic growth rates are more adversely impacted by rising oligopoly costs in the REEs market compared to wealthier economies. Additionally, these countries are negatively affected by China's oligopolistic control over REEs due to weaker bargaining power, reduced economic flexibility, and limited investment in alternative supply chains. Consequently, they bear the full impact of price hikes and trade restrictions without the ability to negotiate better terms, as pointed out by Pan et al. (2021) and Salim et al. (2022). Thus, overreliance on certain countries with REEs endowments can pose a high risk to supply chain security (Salim et al., 2022).

To sum up, the unequal distribution of REEs affects developing countries more than developed ones. Although mines in developed countries find it hard to compete against Chinese REEs activities due to regulatory requirements and high labor and transportation costs (Althaf & Babbitt, 2021; Lee & Wen, 2018), developed economies mitigate this REEs inequality through diversification, technological advancements, strategic reserves, political stability, and more defined socio-economic contexts.

7. Concluding remarks

REEs are critical for producing advanced Information and Communication Technologies (ICTs), renewable energy technologies, and aerospace and military equipment (Massari & Ruberti, 2013; Salim et al., 2022) and constitute limited, non-renewable resources. Their nature imposes significant restrictions on long-term utilization, highlighting the necessity for strategic management of extraction and consumption. As reported by Pan et al. (2021), it is not easy to find deposits that can be extracted economically using current technologies. The politicization around rare earth elements (REEs) has contributed to supply instability, primarily because China and a few other countries, such as Australia, Brazil, India, Russia, the United States, and

Vietnam, have dominated their endowment and use in recent times due to low costs driven by cheap labor and lack of environmental regulations.

This research underscores the critical economic implications of rare earth elements (REEs) in a global market characterized by oligopolistic structures and significant supply instability. The unequal geographical distribution of REEs endowments has amplified disparities between developed and developing countries, with the latter particularly vulnerable to constrained access. As a result, insufficient availability of REEs imposes substantial economic costs, notably in terms of reduced GDP growth—a dynamic that has placed these strategic resources at the center of international policy discourse.

Empirical results from quantile regression provide nuanced insights into the heterogeneous impact of REE-related inequality on economic performance across the growth distribution. Specifically, REE inequality has a weakly negative effect in low-growth (10th percentile) and lower-middle-growth (25th percentile) economies, although these effects are not statistically significant. However, the negative association becomes more pronounced and statistically significant at the median (50th percentile), indicating that inequality in REEs access moderately reduces growth in mid-level economies. In contrast, the relationship shifts direction at higher quantiles: REEs inequality is associated with a moderately significant positive effect at the 75th percentile and a strong, highly significant positive effect at the 90th percentile. These findings suggest that higher-growth economies may benefit from concentrated REE access, potentially due to more effective industrial utilization, technological capacity, or capital-intensive development.

To account for the dynamic structure of economic growth and the endogeneity between inequality and growth outcomes, a one-step system GMM estimator was employed. The results confirm a statistically significant average negative effect of REEs inequality on GDP growth, reinforcing the interpretation that, on balance, inequality in access to strategic resources such as REEs impedes long-term economic development, especially for countries with limited domestic supply.

The dominance of a small group of countries in the REEs market also means that the potential positive externalities from REEs—such as technological spillovers and industrial upgrading—are not evenly distributed globally. This concentration of control exacerbates global inequality and leads to broader social consequences, including economic dependency, social dislocation, and restricted access to essential inputs for green and digital transitions.

Given this context, the objective of this research has been to quantify the growth costs associated with REEs-related vulnerability and strategic dependence. To mitigate these risks, countries—particularly those without domestic REEs production—must adopt proactive technological and policy strategies. These include reducing dependence through innovation (e.g., REEs-efficient technologies), investing in recycling and recovery from electronic waste, and identifying viable substitutes for critical inputs. Such measures not only reduce exposure to external shocks but also promote more inclusive and sustainable growth trajectories in the face of resource asymmetries.

Considering environmental concerns, the extraction of rare earth elements is highly unsustainable due to emissions into the air and water and the generation of solid wastes. Extensive amounts of materials and energy are required for production (e.g., Talens Peiró & Villalba Méndez, 2013; Navarro & Zhao, 2014). Expanding exploration efforts beyond surface deposits offers a viable option for ensuring a stable supply of rare earth elements. Current studies suggest alternative mining options such as deep-sea mining (Dutkiewicz et al., 2020; Hyman et al., 2021) and asteroid mining (Hein et al., 2020). Although they are promising alternative strategies, there is still limited understanding of technological capability, environmental impacts, economic feasibility, and social impacts since they are emerging resources. For example, gold, nickel, manganese, and cobalt, which are necessary for clean energy technologies, can be found in deep-sea mineral deposits. However, this type of extraction is restricted by strong regulations that prevent the negative effects of mining on the marine environment (Dutkiewicz et al., 2020). Asteroid mining is considered a promising alternative for obtaining rare earth elements (REEs) due to the high concentration of REEs on asteroids. Additionally, space mining, considering also current technological limitations, is believed to have lower environmental impacts compared to terrestrial mining, although the impact on space has not been fully understood (Hein et al., 2020).

We conclude that it is essential for policymakers to prioritize REEs recycling technologies as a cornerstone of future development strategies. Fostering progress in recycling technologies for REEs can help reduce some adverse impacts linked to the oligopolistic nature of the market and contribute to a fairer distribution of societal benefits. While this measure alone might not be sufficient to bridge the gap between supply and demand, it could represent significant aid in the long run. A promising avenue for further research is the quantitative investigation of the impact of recycling policies on the global supply and their beneficial effects in the energy market.

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Appendix A

Table A.1
Data Source

Variable	Description	Source
Gdp_growth_rate (%)	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on the constant 2010 U.S. dollar.	World Bank and OECD
Gdppc_growth_rate (%)	GDP per capita is gross domestic product divided by midyear population. Data are in constant local currency.	World Bank and OECD
Inequality_REEs	Built authors' index. Normalized distance between a country's REEs endowments and those of reference countries with REEs, such as China and a few others. Assumes value 1 for countries placed at a greater distance from the reference countries with high levels of REEs endowment, and 0 otherwise	Author's elaboration
Investment_cash_flow	(% of GDP) Net cash used for or generated by investment activities within a country's economy, expressed relative to the country's Gross Domestic Product (GDP). It provides insight into the scale of investment activity compared to the overall size of the economy.	World Bank
Mineral depletion rate (%)	Ratio of the value of the stock of mineral resources to the remaining reserve lifetime (capped at 25 years). It covers tin, gold, lead, zinc, iron, copper, nickel, silver, bauxite, and phosphate.	World Bank
Fossil fuel consumption rate (%)	(% of total) Fossil fuel comprises coal, oil, petroleum, and natural gas products	IEA Statistics © OECD

(continued on next page)

Table A.1 (*continued*)

Variable	Description	Source
R&D expenditures rate (%)	Gross domestic expenditure on research and development (R&D), expressed as a percentage of GDP. They include both capital and current expenditures in the four main sectors: Business enterprise, Government, Higher education and Private non-profit. R&D covers basic research, applied research, and experimental development	UNESCO Institute for Statistics (UIS)
Education (%)	Adjusted net enrollment rate, primary (% of primary school age children) - Adjusted net enrollment is the number of pupils of the school-age group for primary education, enrolled either in primary or secondary education, expressed as a percentage of the total population in that age group	UNESCO Institute for Statistics (UIS)
Patents (%)	(% of total) Ratio of number of resident patents over total (resident and non-resident patents) filed through the Patent Cooperation Treaty procedure or with a national patent office	World Intellectual Property Organization (WIPO)
Corruption	Index that captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator, with 0 corresponding to lowest rank, and 100 to highest rank. Percentile ranks have been adjusted to correct for changes over time in the composition of the countries covered by the WGI	The WGI produced by Kaufmann and Kraay*
Political stability	Index that captures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism. Estimate gives the country's score in units of a standard normal distribution, i.e. ranging from approximately −2.5–2.5	The WGI produced by Kaufmann and Aart*
Population	Total population between the ages 15–64. Population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship	Word Bank

*For more details see: Kaufmann, D., Aart K. and Mastruzzi, M., (2010). "The Worldwide Governance Indicators: Methodology and Analytical Issues". World Bank Policy Research Working Paper No. 5430 (http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1682130)

Table A.2
Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Gdp_growth_rate	2578	3.089	4.974	-41.8	88.958
Gdppc_growth_rate	2578	2.394	4.865	-41.099	81.355
Inequality_REEs	2578	.958	.154	0	1
Investment_cash_flow	2578	1.276	4.748	-76.771	36.171
Mineral depletion rate	2578	.223	1.001	0	30.455
Fossil fuel consumption rate	2578	75.419	20.913	8.595	99.905
R&D expenditures	2578	1.214	.907	.013	3.874
Education	2578	94.545	6.685	51.889	100
Patents	2578	.468	.328	.005	.997
Corruption	2578	62.731	28.416	0	100
Political stability	2578	.34	.762	-2.212	1.964
Country_id	2578	31.5	17.898	1	62
Year	2578	1997.5	14.433	1973	2022

Table A.3
Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) gdpgrow	1.000										
(2) gdppc_growr	0.976	1.000									
(3) inequality_REEs	-0.162	-0.140	1.000								
(4) patent_nores_p	0.117	0.015	-0.068	1.000							
(5) inv_cash_flow	0.116	0.141	-0.027	0.065	1.000						
(6) school	-0.144	-0.101	0.001	0.014	-0.069	1.000					
(7) mdr	0.040	0.025	-0.018	0.163	0.067	0.038	1.000				
(8) corruption	-0.199	-0.221	0.258	-0.144	-0.279	0.268	-0.041	1.000			
(9) ffec	-0.083	-0.056	0.098	-0.047	0.016	0.002	0.017	-0.216	1.000		
(10) polsta	-0.144	-0.133	0.126	-0.069	-0.183	0.345	-0.076	0.707	-0.066	1.000	
(11) rdexp	-0.206	-0.222	-0.009	-0.282	-0.300	0.158	-0.157	0.685	-0.321	0.528	1.000

Table A.4.1
Partial and semipartial correlation with gdpgrowth

	Partial Corr.	Semipartial Corr.	Partial Corr.^2	Semipartial Corr.^2	Significance Value
Inequality_REEs	-0.009	-0.009	0.000	0.000	0.828
Inv_cashflow	0.082	0.078	0.007	0.006	0.053
Mineral depletion	0.051	0.048	0.003	0.002	0.237
Fossil Fuel cons.	-0.049	-0.046	0.002	0.002	0.252
R&D expenditure	-0.067	-0.063	0.004	0.004	0.117
Education	-0.147	-0.140	0.022	0.020	0.001
Patents	0.047	0.044	0.002	0.002	0.269
Corruption	-0.087	-0.083	0.008	0.007	0.040
Political Stability	0.005	0.005	0.000	0.000	0.905

Table A.4.2
Partial and semipartial correlation with gdppc_growth

	Partial Corr.	Semipartial Corr.	Partial Corr.^2	Semipartial Corr.^2	Significance Value
Inequality_REEs	-0.004	-0.004	0.000	0.000	0.926
Inv_cashflow	0.113	0.105	0.013	0.011	0.008
Mineral depletion	0.027	0.025	0.001	0.001	0.521
Fossil Fuel Cons	-0.089	-0.083	0.008	0.007	0.038
R&D expenditure	-0.107	-0.100	0.012	0.010	0.012
Education	-0.157	-0.147	0.025	0.022	0.000
Patents	-0.030	-0.028	0.001	0.001	0.487
Corruption	-0.085	-0.079	0.007	0.006	0.047
Political Stability	0.008	0.007	0.000	0.000	0.852

Appendix B

Table B.1
Univariate quantile regression with bootstrapped standard errors

	(1)	(2)	(3)	(4)	(9)
Quantiles	.10	.25	.50	.75	.90
Dependent Variable	gdpgrowthr	gdpgrowthr	gdpgrowthr	gdpgrowthr	gdpgrowthr
HHI_index	-5.136***	-3.409***	-2.835***	0.748	0.0557
	(1.557)	(0.711)	(0.218)	(1.618)	(0.866)
Constant	2.222	4.178***	7.029***	10.94***	12.25***
	(1.566)	(1.058)	(0.719)	(1.583)	(0.999)
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	2578	2578	2578	2578	2578

Note: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.2
Univariate quantile regression with bootstrapped standard errors

	(1)	(2)	(3)	(4)	(5)
Quantiles	.10	.25	.50	.75	.90
Dependent Variable	gdppc_growthr	gdppc_growthr	gdppc_growthr	gdppc_growthr	gdppc_growthr
HHI_index	-4.365*	-2.031	-1.252***	0.263	2.115***
	(2.444)	(1.665)	(0.409)	(2.015)	(0.533)
Constant	3.809***	3.795	7.081***	9.701***	12.99***
	(1.003)	(2.608)	(0.390)	(2.012)	(0.564)
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	2578	2578	2578	2578	2578

Note: Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.3
Multivariate quantile regression with bootstrapped standard errors – gdpgrowth

	(1)	(2)	(3)	(4)	(5)
Quantiles	.10	.25	.50	.75	.90
Dependent Variable	gdpgrowthr	gdpgrowthr	gdpgrowthr	gdpgrowthr	gdpgrowthr
HHI_index	-5.576	-2.386	-6.345	7.586***	9.694***
	(6.275)	(3.172)	(4.488)	(2.606)	(3.491)
inv_cash_flow	0.080	0.091**	0.002	-0.026	-0.015
	(0.057)	(0.041)	(0.069)	(0.047)	(0.041)
mdr	0.177	0.214	0.010	0.093	-0.320
	(0.481)	(0.460)	(0.459)	(0.390)	(0.462)
ffec	-0.015	-0.024	-0.022	-0.029	-0.041
	(0.048)	(0.05)	(0.039)	(0.033)	(0.032)
RDexp	-0.759	0.123	0.227	-0.425	-0.547
	(0.858)	(1.036)	(1.007)	(0.654)	(0.674)
school	0.108	0.095	0.062	0.089	0.158*
	(0.078)	(0.084)	(0.088)	(0.068)	(0.087)
patent_nores_p	2.347	0.844	0.784	0.278	-0.012
	(1.445)	(0.963)	(1.055)	(0.919)	(1.042)
corruption	0.011	-0.020	0.064	0.067*	0.083**
	(0.035)	(0.044)	(0.048)	(0.039)	(0.038)

(*continued on next page*)

Table B.3 (*continued*)

	(1)	(2)	(3)	(4)	(5)
Quantiles	.10	.25	.50	.75	.90
Dependent Variable	gdpgrowthr	gdpgrowthr	gdpgrowthr	gdpgrowthr	gdpgrowthr
political stability	1.729**	1.787	1.390*	0.466	1.348**
	(0.873)	(1.281)	(0.772)	(0.952)	(0.644)
Constant	-14.87*	-7.375	-2.213	-0.405	-5.232
	(8.090)	(8.758)	(10.84)	(7.136)	(9.977)
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	2578	2578	2578	2578	2578

Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.4
Multivariate quantile regression with bootstrapped standard errors – gdppcgrowth

	(1)	(2)	(3)	(4)	(5)
Quantiles	.10	.25	.50	.75	.90
dependent variable	gdppc_growthr	gdppc_growthr	gdppc_growthr	gdppc_growthr	gdppc_growthr
HHI_index	-6.151*	-1.783	-5.073*	7.360**	8.087*
	(3.647)	(3.386)	(2.729)	(3.325)	(4.408)
inv_cash_flow	0.071	0.094*	0.047	-0.027	-0.025
	(0.044)	(0.052)	(0.036)	(0.060)	(0.034)
mdr	0.122	0.093	0.045	-0.268	-0.464
	(0.393)	(0.288)	(0.299)	(0.442)	(0.298)
ffec	0.013	-0.024	-0.056	-0.006	-0.049
	(0.059)	(0.043)	(0.041)	(0.043)	(0.036)
rdexp	-0.728	-0.080	0.011	-0.430	-0.777
	(0.650)	(0.881)	(0.931)	(0.595)	(1.214)
school	0.133	0.121	0.064	0.084	0.122
	(0.083)	(0.098)	(0.081)	(0.087)	(0.099)
patent_nores_p	1.724	1.296	0.986	-0.160	-0.292
	(1.314)	(1.107)	(0.810)	(0.908)	(1.072)
corruption	-0.002	0.005	0.0480	0.068	0.076
	(0.027)	(0.039)	(0.047)	(0.051)	(0.049)
political stability	1.867	1.743*	1.702**	0.544	0.852
	(1.632)	(0.941)	(0.765)	(0.965)	(0.744)
Constant	-19.09	-11.31	-0.00254	-3.018	-1.931
	(11.75)	(10.78)	(10.64)	(10.05)	(10.96)
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	2578	2578	2578	2578	2578

Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.5
Instrumental Variables (IV) estimated results

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4b)	(4a)	(5a)	(5b)
Quantiles	.10	.10	.25	.25	.50	.50	.75	.75	.90	.90
Dependent Variable	gdpgrowth	gdppc_growth	gdpgrowth	gdppc_growth	gdpgrowth	gdppc_growth	gdpgrowth	gdppc_growth	gdpgrowth	gdppc_growth
Inequality_REEs	-7.779***	-6.598***	-6.802***	-5.049***	-6.198***	-6.155***	-5.531***	-2.995***	-4.788***	-1.762***
	(0.968)	(1.187)	(0.730)	(0.861)	(0.719)	(0.618)	(0.840)	(0.553)	(1.081)	(0.525)
Constant	5.743***	3.793***	7.846***	5.380***	9.145***	9.015***	10.58***	7.482***	12.18***	8.745***
	(0.927)	(1.118)	(0.686)	(0.810)	(0.677)	(0.677)	(0.796)	(0.510)	(1.028)	(0.468)
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2309	2309	2309	2309	2309	2309	2309	2309	2309	2309

Note: Standard errors *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; *landcer* is the instrument used for Inequality_REEs;

Table B.6
Instrumental Variables (IV) estimated results – with interaction term for developing countries

	(1)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(5a)	(5b)
Quantile	.10	.10	.25	.25	.50	.50	.75	.75	.90	.90
Dependent Variable	gdpgrowth	gdppc_growth	gdpgrowth	gdppc_growth	gdpgrowth	gdppc_growth	gdpgrowth	gdppc_growth	gdpgrowth	gdppc_growth
Inequality_REEs	-9.532***	-6.935***	-8.885***	-6.471***	-7.863***	-6.431***	-6.060***	-4.723***	-4.609***	-2.269***
	(2.151)	(1.364)	(0.698)	(1.178)	(0.714)	(0.752)	(0.637)	(0.624)	(0.835)	(0.389)
Dummy_developing	-6.323*	-5.004**	-3.993***	-1.620	-2.482***	-1.499**	-0.115	0.825	1.235	3.137***
	(3.586)	(2.010)	(1.181)	(1.698)	(0.655)	(0.758)	(0.769)	(0.629)	(1.300)	(0.980)
Inequality*developing	-3.926	-2.035	-4.235***	-1.330	-4.037***	-2.961***	-2.332***	-1.331**	-1.885	-0.467
	(3.623)	(2.182)	(1.099)	(1.756)	(0.674)	(0.754)	(0.853)	(0.602)	(1.358)	(0.968)
Constant	8.561***	5.397***	9.944***	6.947***	10.35***	8.315***	10.15***	8.265***	10.42***	7.604***
	(2.109)	(1.284)	(0.698)	(1.165)	(0.706)	(0.738)	(0.610)	(0.619)	(0.807)	(0.247)
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2578	2578	2578	2578	2578	2578	2578	2578	2578	2578

Note: Standard errors *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.7
Results with one-step System GMM

	(1) All countries gdpgrowth	(2) All countries gdppc_growth
L.gdpgrow	.3988***	
	{0.073}	
L.gdppc_growr		.3995***
		{0.070}
REEs_inequality	-2.611**	-2.567**
	{1.080}	{1.020}
Constant	2.828	1.764
	{8.749}	{9.031}
Others controls	YES	YES
Country FE	YES	YES
Year FE	YES	YES
Observartions	1557	1557
A-B test (1)	0.000	0.000
A-B test (2)	0.184	0.169
Hansen (p-value)	0.174	0.165

Note: Standard errors *** p < 0.01, ** p < 0.05, * p < 0.1

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